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A Proposed Artificial Intelligence Algorithm for Assessing of Risk Priority for Medical Equipment in Iraqi Hospital

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Abstract

This paper presents a robust algorithm for the assessment of risk priority for medical equipment based on the calculation of static and dynamic risk factors and Kohnen Self Organization Maps (SOM). Four risk parameters have been calculated for 345 medical devices in two general hospitals in Baghdad. Static risk factor components (equipment function and physical risk) and dynamics risk components (maintenance requirements and risk points) have been calculated. These risk components are used as an input to the unsupervised Kohonen self organization maps. The accuracy of the network was found to be equal to 98% for the proposed system. We conclude that the proposed model gives fast and accurate assessment for risk priority and it works as promising tool for risk factor assessment for the service departments in large hospitals in Iraq.

Keywords: Risk factors, Neural Networks, SOM, and Risk Priority**.**

1. Introduction

Inherent in the definition of risk management is the implication that the hospital environment cannot be made risk-free. In fact, the nature of medical equipment to invasively or noninvasively perform diagnostic, therapeutic, corrective, or monitoring intervention on behalf of the patient implies that risk is present. Therefore, a standard of acceptable risk must be established that defines manageable risk in a real-time economic environment.

Risk factors that require management can be illustrated by the example of the "double-edge" sword concept of technology (see Fig.1) [1, 2].

For example, the purchase and installation of a major medical equipment may only represent 20% of the lifetime cost of the equipment [3]. If the operational budget of a nursing floor does not include the other 80% of the equipment costs, the budget constraints may require cutbacks where they appear to minimally affect direct patient care. Preventive maintenance, software upgrades that address "glitches," or overhaul requirements may be seen as unaffordable luxuries. Gradual equipment deterioration without maintenance may bring the safety level below an acceptable level of manageable risk.

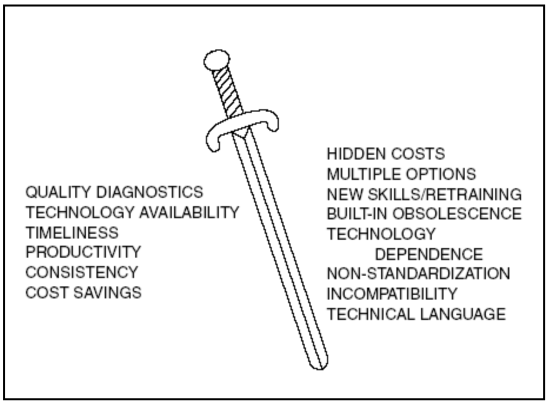

Fig.1. Double-Edged Sword Concept of Risk Management.

One computer technique under investigation is the artificial neural network [4,5]. Neural networks are tools for multivariate analysis that can be used to estimate disease risk. They are able to model complex nonlinear systems with significant variable interactions. Theoretical work suggests that neural networks may be able to consistently match or exceed the performance of traditional statistical methods [6]. Neural networks have been used effectively in several clinical studies, in areas including the evaluation of radiological studies [7], the diagnosis of acute illness [8], the prediction of intensive- care-unit length of stay [9], the diagnosis of appendicitis [10], the diagnosis of psychiatric disorders [11,12] and the diagnosis of acute pulmonary embolism [13].

In Urology, There is a good example of NN application to diagnose prostate cancer [14]. The purpose of this study is to develop a Kohonen-SOM network which will determine the risk priority based on the input components of static and dynamics risk factors. This network will act to help in the assessment of risk problems for medical devices for the large Iraqi hospitals.

2. Risk Management

To apply risk management to the department of clinical engineering, one must understand the basic components of the risk management process. The process consists of five steps [15]:

1. Identify and analyze exposures.
2. Consider alternative risk treatments techniques.
3. Select the best technique to manage and treat the risk.
4. Implement the selected technique.
5. Monitor and improve the risk management program risk management program.

Reactive risk management is an outgrowth of the historical attitude in medical equipment management that risk is an anomaly that surfaces in the form of a failure. If the failure is analyzed and proper operational procedures such as, user in-services, and increased maintenance are supplied, the problem will disappear and the person can return to their normal work. When the next failure occurs, the algorithm is repeated. If the same equipment fails, the algorithm is applied more intensely. This is a useful but not comprehensive component of risk management in the hospital. In fact, the traditional methods of predicting the reliability of electronic equipment from field failure data have not been very effective [1, 16].

The health care environment, as previously mentioned, inherently contains risk that must be maintained at a manageable level. A reactive tool cannot provide direction to a risk-management program, but it can provide feedback as to its efficiency.

Obviously, a more forward-looking tool is needed to take advantage of the failure codes and the plethora of equipment information available in a clinical engineering department. This proactive tool should use failure codes, historical information, the “expert” knowledge of the clinical engineer, and the baseline of an established “manageable risk” environment (perhaps not optimal but stable).

The overall components and process flow for a proactive risk-management tool are presented in Fig. 2 [1]. It consists of a two-component static risk factor, a two-component dynamic risk factor, and to two different static risk and two “shaping” or feedback loops.

2.1. Static Risk Factors

The static risk factor classifies new equipment by a generic equipment type: defibrillator, electrocardiograph, pulse oximeter, etc. When equipment is introduced into the equipment database, it is assigned to two different static risk (Fig. 3) categories [1,2].

The first is the equipment function that defines the application and environment in which the equipment item will operate. The degree of interaction with the patient is also taken into account. For example, a therapeutic device would have a higher risk assignment than a monitoring or diagnostic device.

The second component of the static risk factor is the physical risk category. It defines the worst-cases scenario in the event of equipment malfunction.

The correlation between equipment function and physical risk on many items might make the two categories appear redundant. However, there are sufficient equipment types where there is not the case.

A scale of 1–25 is assigned to each risk category. The larger number is assigned to devices demonstrating greater risk because of their function or the consequences of device failure. The 1–25 scale is an arbitrary assignment, since a validated scale of risk factors for medical equipment, as previously described, is nonexistent. The risk points assigned to the equipment from these two categories are algebraically summed and designated the static risk factor. This value remains with the equipment type and the individual items within that equipment type permanently. Only if the equipment is used in a clinically variant way or relocated to a functionally different environment would this assignment be reviewed and changed.

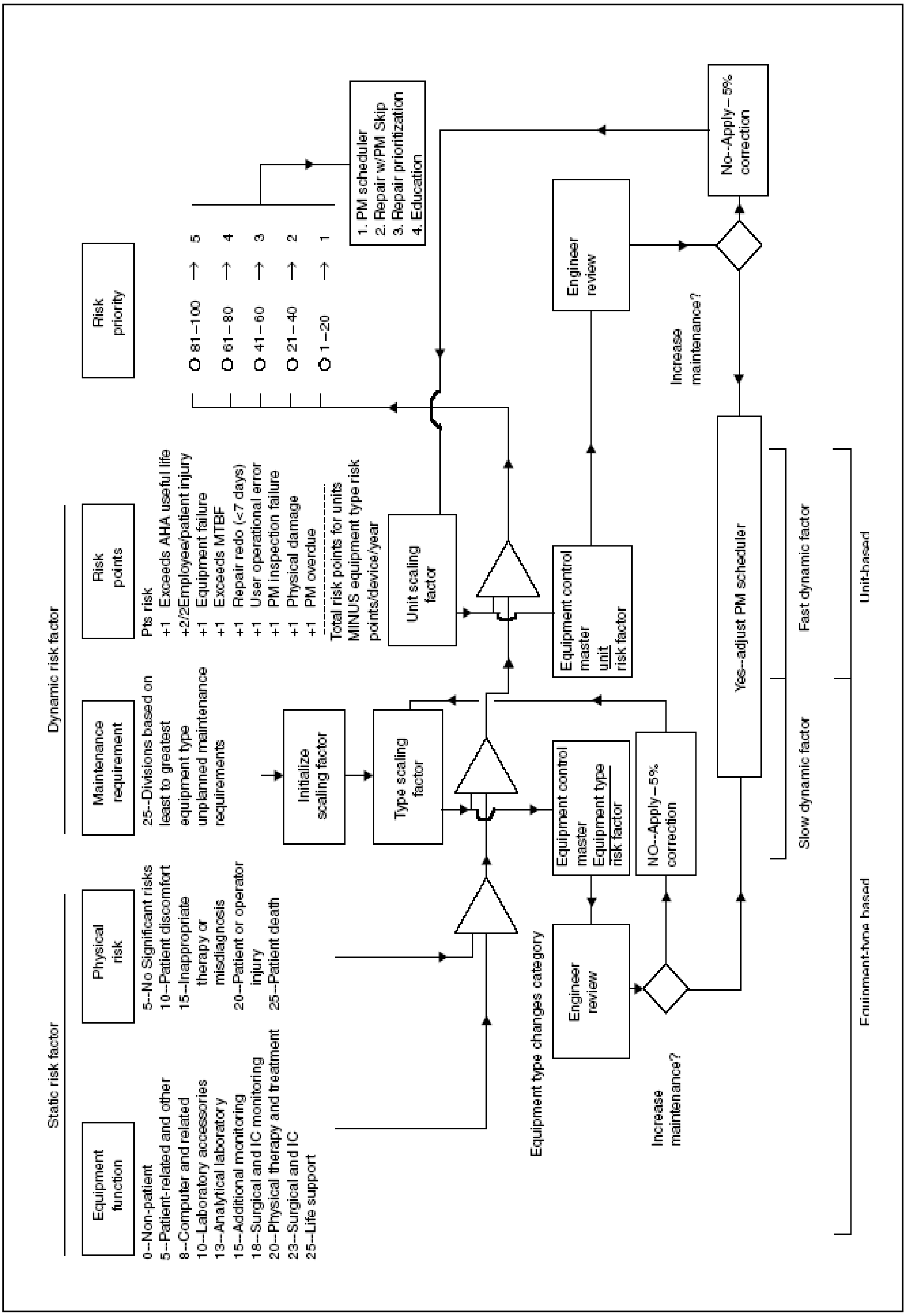

Fig.2. Biomedical Engineering Risk-Management Tool [1].

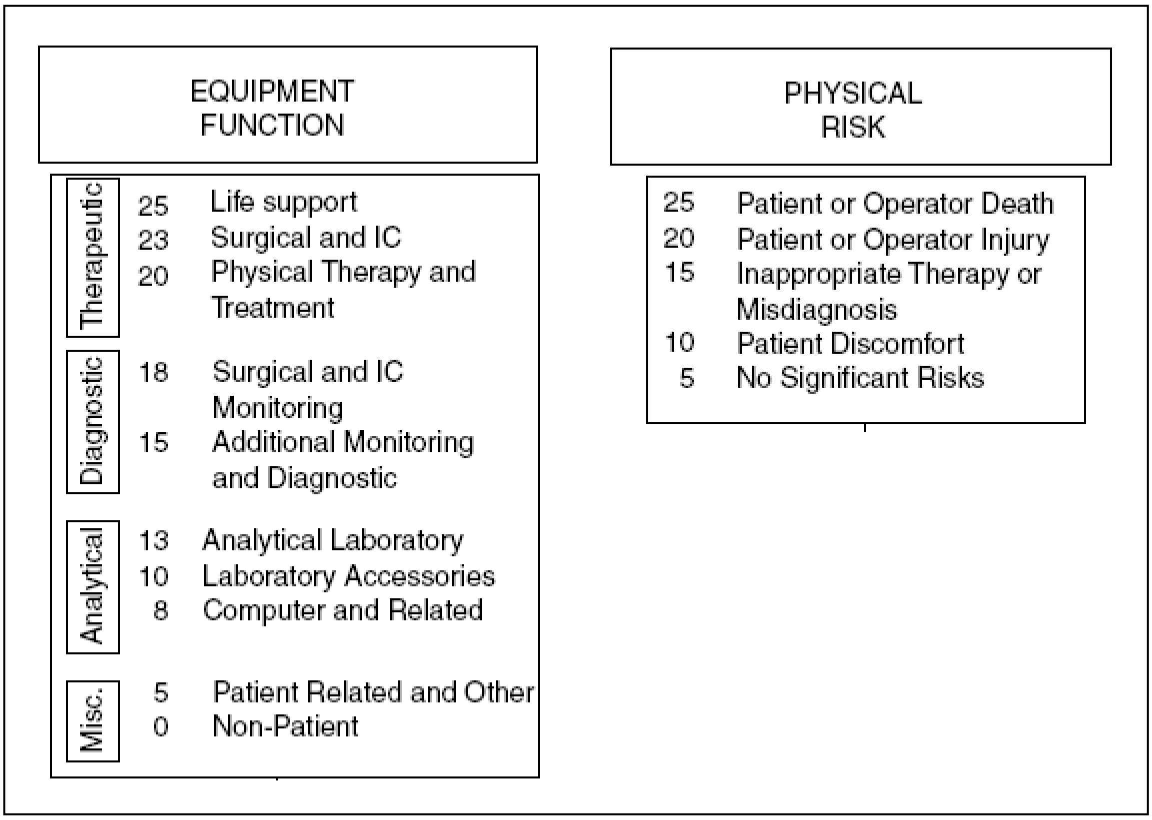

Fig.3. Static Risk Components.

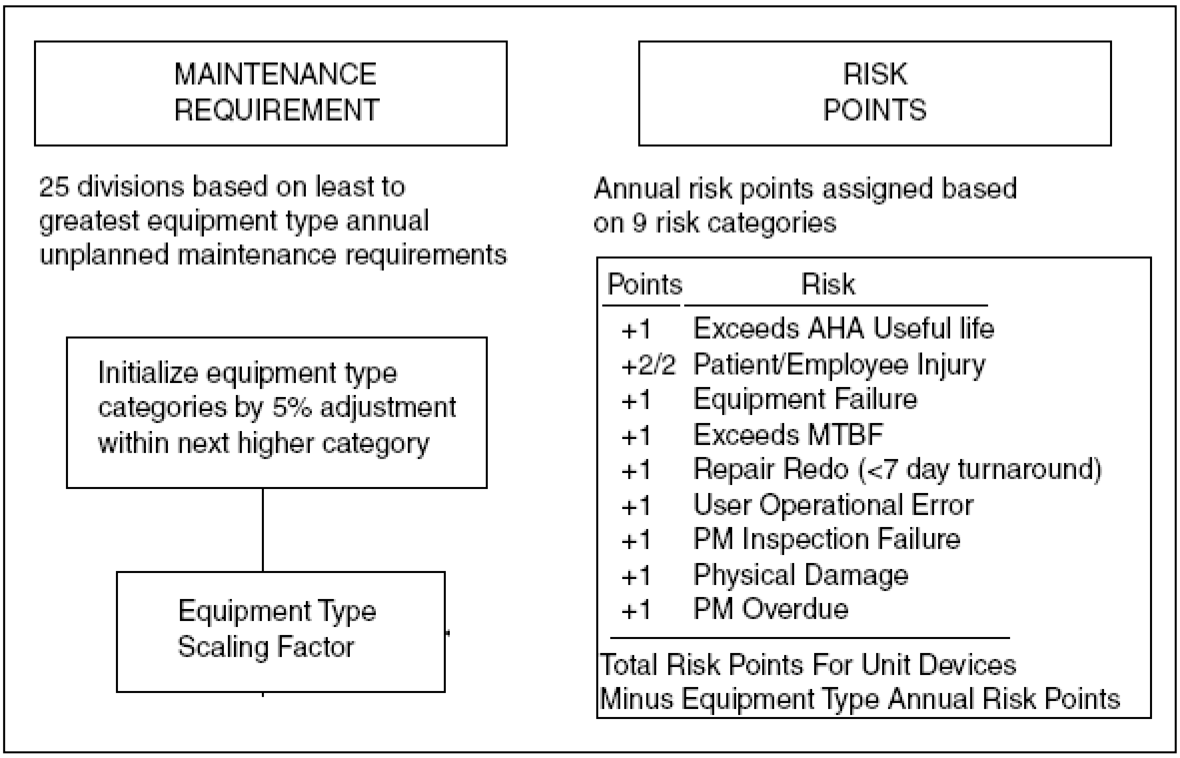

Fig.4. Dynamic Risk Components.

2.2. Dynamic Risk Factors

The dynamic component (Fig. 4) of the risk-management tool consists or two parts [1, 2].
The first is a maintenance requirement category that is divided into 25 equally spaced divisions, ranked by least (1) to greatest (25) average man hours per device per year. These divisions are scaled by the maintenance hours for the equipment type requiring the greatest amount of maintenance attention. The amount of non planned (repair) man hours from the previous 12 months of service reports is totaled for each equipment type.

The second dynamic element assigns weighted risk points to individual equipment items for each unique risk occurrence. An occurrence is defined as by one of the following points:

- Device exceeds the American Hospital Association Useful Life Table for Medical Equipment or exceeds the historical Mean Time Before Failure (MTBF) for that manufacturer and model
- Device injures a patient or employee
- Device functionally fails or fails to pass a PM inspection
- Device is returned for repair or returned for repair within 9 days of a previous repair occurrence
- Device misses a planned maintenance inspection
- Device is subjected to physical damage
- Device was reported to have failed but the problem was determined to be a user operational error.

3. Theory of Self Organization Maps

Kohonen networks or self-organizing feature maps are networks, which consist only of two layers, an input and an output layer. The output layer of Kohonen networks can be two-dimensional. The most important difference is that the neurons of the output layer are connected with each other. The arrangement of the output neurons plays an important role. Sensorial input signals, which are presented to the input layer, cause an excitation of the output neurons, which is restricted to a zone of limited extent somewhere in the layer. This excitation behavior comes from the back coupling of the neurons. It is essential to know how the interconnections of the neurons have to be organized in order to optimize the spatial distribution of their excitation behavior over the layer. Neurons with similar tasks can communicate over very short pathways.

The SOM algorithm is based on unsupervised, competitive learning. It provides a topology preserving mapping from the high dimensional space to map units. Map units, or neurons, usually form a two-dimensional lattice and thus the mapping is a mapping from high dimensional space onto a plane. The property of topology preserving means that the mapping preserves the relative distance between the points. Points that are near each other in the input space are mapped to nearby map units in the SOM. The SOM can thus serve as a cluster analyzing tool of high-dimensional data. Also, the SOM has the capability to be generalized. Generalization capability means that the network can recognize or characterize inputs as it has never encountered before. A new input is assimilated with the map unit it is mapped to.

The optimization produces topographic maps of the input signals, in which the most important relationships of similarity between the input signals are converted into relationships among the neuron positions. This corresponds to an abstracting capability which suppresses unimportant details and maps the most important features along the map dimension. Summarized, one can say that Kohonen networks seek to transpose the similarity of sensorial input signals to the neighborhood of neuron positions.

The proposed SOM algorithm is based on the conventional SOM algorithm developed by Kohonen [17] [18]. A sketch of a SOM topology is shown in fig. 5. The SOM algorithm for classification is summarized by the following steps:

a. **Initialize input nodes, output nodes, and connection weights:** Use the top (most frequently occurring) N terms as the input vector and create a two-dimensional map (grid) of M output nodes. Initialize weights w_{ij} from N input nodes to M output nodes to small random values.
b. **Present each set in order:** Describe each set as an input vector of N coordinates..
c. **Compute distance to all nodes:** Compute Euclidean distance d_j between the input vector and each output node j:

$$d_j = \sum_{i=0}^{N-1} (x_i(t) - w_{ij}(t))^2 \qquad \dots (1)$$

where $x_i(t)$ can be 1 or 0 depending on the presence of i-th term in the document presented at time t. Here, w_{ij} is the vector representing position of the map node j in the document vector space. From a neural net perspective, it can also be interpreted as the weight from input node i to the output node j.

d. Select winning node j^* and update weights to node j^* and its neighbors: Select winning node j^*, which produces minimum d_j. Update weights to nodes j^* and its neighbors to reduce the distances between them and the input vector $x_i(t)$:

$$w_{ij}(t+1) = w_{ij}(t) + \eta(t)(x_i(t+1) - w_{ij}(t)) \quad \dots (2)$$

Where $\eta(t)$ is the learning parameter. After such updates, nodes in the neighborhood of j^* become more similar to the input vector $x_i(t)$. Here, $\eta(t)$ is an error-adjusting coefficient ($0 < \eta(t) < 1$) that decreases over time.

For the neurons that lose the competition as:

$$w_{ij}(t+1) = w_{ij}(t) \quad \dots (3)$$

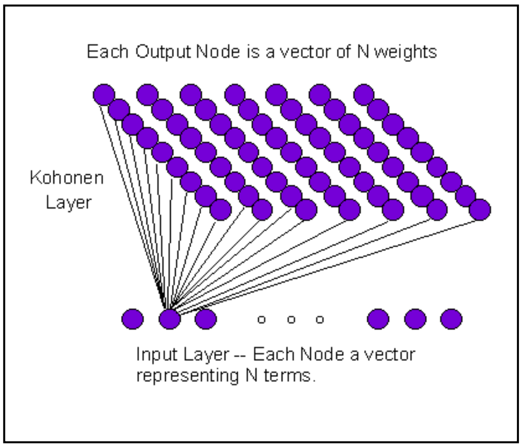

Fig.5. Kohonen SOM Topology

Kohonen's SOM or a feature map [19] provides us with classification rules. SOM combines competitive learning with dimensionality reduction by smoothing clusters with respect to an a priori grid. With SOM, clustering is generated by having several units compete for (training) data The unit whose weight vector is closest to the data becomes the winner so as to move even closer to the input data, the weights of the winner are adjusted as well as those of the nearest neighbors. This is called Winner Takes All (WTA) approach. SOM assumes some topology among the input data. The organization is said to form a SOM map because similar inputs are expected to put closer position with each other. The flow chart of SOM algorithm is shown in fig.6 [20].

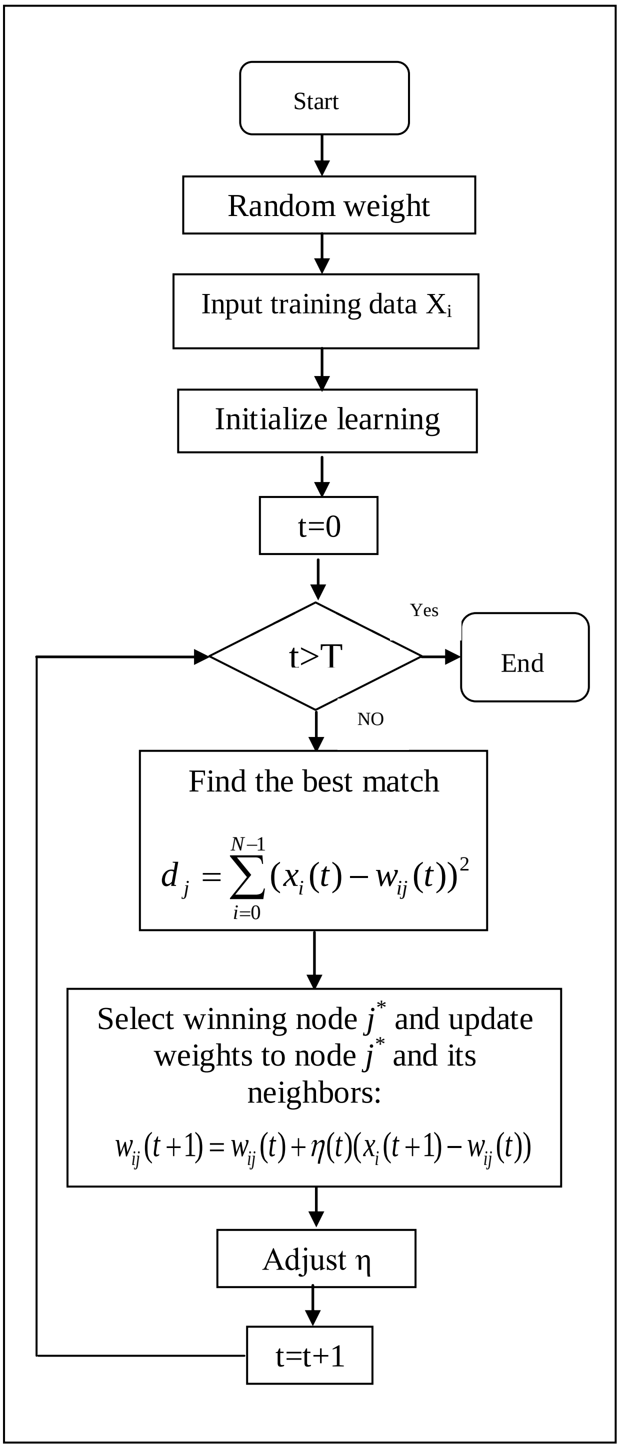

Fig.6. Flow Chart of SOM Algorithm [20]

4. Data Collection and Methods Used

In this study, our survey took two large general hospitals in Baghdad. (Al Yarmmok Teaching Hospital and Shaheed Adnan Hospital for Specialized Surgeries).

A report is prepared which contains the coding of the static and dynamic risk components. These codes will be used for calculation of the risk factor components. The period for collecting these reports is from September- 2008 to November-2008.

345 reports for different medical equipment were collected from these hospitals with the help of the biomedical engineer in the service department at these hospitals. A variety of medical equipments are included in our research starting from small to large, simple to complex and analytic to therapeutic equipments.

A sample of the collected reports for the calculation of risk factors components calculation is shown in Fig. 7.

These reports are analyzed and coded to calculate the following risk components:

- **i. Equipments function.**
- **ii. Physical risk**
- **iii. Maintenance requirements.**
- **iv. Risk points.**

The risk components report is taken from the biomedical engineer at the above mentioned hospitals.

The total amounts of cases for all reports in this study have been divided into two groups. One for the training process (290 cases) and the other group for testing of the proposed network (55 cases). MATLAB Software package version 7 is used to implement the software for the current work. A sample of the testing data for forty cases is shown in Table 1.

A total set of 345 feature vectors each one with four risk components is prepared to be as an input to the proposed SOM. Then the SOM network will give us the risk priorities based on the input data.

5. Training and Testing

The network was trained with all of 290 training data sets. These 290 training data sets are fed to the Kohonen SOM with four neurons.

The Kohonen learning rate is set to 0.01. The output of the SOM network was 1,2,3,4 and 5; this means that we have a 1st, 2nd, 3rd, 4th and 5th degree of risk priority respectively. The 1st and the 5th degree of risk priority represent the minimum and maximum risk priority whereas the 3rd degree represents the moderate risk degree. The remaining 2nd and 4th degree are the low and high risk priority.

The training set is grouped into one matrix with dimension of (290x4). This matrix is fed to the input layer of SOM.

After 100 epochs, the network finished the training process. When the training process is completed for all of the training data sets (290 cases), the last weights of the network were saved to be ready for the testing procedure. The training process took 7.1 second.

The testing process is done for 55 data sets. These 55 data sets are fed to the network and their output is recorded for calculation of the accuracy of the network. The time for running the algorithm for testing process was 1.3 second.

6. Results and Discussion

The performance of the algorithm was evaluated by computing the percentage and accuracy of the network. The definition of accuracy of proposed network is [21]:

$$\text{Accuracy} = \frac{\text{Correct identification}}{\text{Total no. of cases}} \times 100\% \quad \dots (4)$$

The obtained accuracy of assessment with the time to run the algorithm is shown in Table 2.

In our study, the use of SOM has been proposed for risk priority assessment for medical equipments by means of calculating the risk factors components (Equipments, function, physical risk, maintenance requirements and risk points) from reports of risk factors. The obtained accuracy of proposed network was found to be 98%. This means that the proposed model falls only one time to assess the risk priority (only one misidentification from the total 55 set of testing data). This is regarded a very robust and the system is reliable when there is a little number of misclassification. The time needed to test the proposed algorithm was 1.3 sec. which is relatively short time and can be helpful in minimizing the time needed to assess the status of risk of the medical equipment in the hospitals. Based on the obtained result, it showed that the algorithm can be reliable purposes in the service departments of large hospitals.

Report of the Calculation of Static and Dynamic Risk Factors

Name of the hospital: Al-Yarmook Teaching Hospital

Reference: Testing 14

Name of the medical Device: Cardiac Moniter

Date: 16-September -2008

Type (Therapeutic, Diagnostic, Analytic and Misc.): Diagnostic

Device size and complexity (Small, Medium and large): Small

EQUIPMENT FUNCTION

Therapeutic	25	Life support
	23	Surgical and IC
	20	Physical Therapy and Treatment
Diagnostic	18	Surgical and IC Monitoring
	15	Additional Monitoring and Diagnostic
Analytical	13	Analytical Laboratory
	10	Laboratory Accessories
	8	Computer and Related
Misc.	5	Patient Related and Other
	0	Non-Patient

PHYSICAL RISK

25	Patient or Operator Death
20	Patient or Operator Injury
15	Inappropriate Therapy or Misdiagnosis
10	Patient Discomfort
5	No Significant Risks

MAINTENANCE REQUIREMENT

25 divisions based on least to greatest equipment type annual unplanned maintenance requirements

RISK POINTS

Annual risk points assigned based on 9 risk categories

Points	Risk
+1	Exceeds AHA Useful life
+2/2	Patient/Employee Injury
+1	Equipment Failure
+1	Exceeds MTBF
+1	Repair Redo (<7 day turnaround)
+1	User Operational Error
+1	PM Inspection Failure
+1	Physical Damage
+1	PM Overdue

Total Risk Points For Unit Devices Minus Equipment Type Annual Risk Points

$$\text{Risk points} = 3/9*25 = 8$$

	Static Risk Factor		Dynamic Risk Factor	
Device Name	Equipment Function	Physical Risk	Maintenance Requirement	Risk Points
Cardiac Monitor	18	15	10	8

Fig.7. Sample of the Report of the Calculation of Risk Factors Used in the Work

Table 1,
Data Used for Testing of the SOM Network

No.	Device Name	Equip. Function	Physical Risk	Maintenance. Requirements	Risk Points	Risk Factor	Risk Priority	Output of SOM
1	Carbon dioxide gas analyzer	13	15	5	0	33	2	2
2	Carbon monoxide gas analyzer	13	15	5	0	33	2	2
3	Oxygen gas analyzer	13	15	5	3	36	2	2
4	Monitoring spirometer	15	15	5	0	35	2	2
5	Gas pressure gauge	10	15	4	0	29	2	2
6	Anesthesia breathing circuit	25	20	10	0	55	3	3
7	Breathing gas mixer	25	20	10	0	55	3	3
8	Electro anesthesia apparatus	25	20	12	3	60	3	3
9	Nebulizer	20	15	5	0	40	2	2
10	Noninvasive blood pressure measurement system	10	15	9	3	37	2	2
11	Densitometer	15	15	3	6	39	2	2
12	Angiographic injector	10	5	6	6	27	2	2
13	Stethoscope	5	5	0	0	10	1	1
14	Cardiac monitor	18	15	11	8	52	3	3
15	Ultrasound	18	15	3	6	42	3	3
16	Electrocardiograph	18	20	3	12	53	3	3
17	Phonocardiograph	15	10	6	3	34	2	2
18	Pulse Oximeter	15	15	2	3	35	2	2
19	Intra-aortic balloon	25	25	17	14	81	5	5
20	External pacemaker	23	20	2	14	59	3	3
21	Implantable pacemaker	23	20	2	14	59	3	3
22	DC-defibrillator	23	25	5	14	67	4	4
23	Blood PCO2, PO2 test system	13	15	3	7	38	2	2
24	Total Cholesterol test system.	13	15	3	7	38	2	2
25	Creatine test system	13	15	3	8	39	2	2
26	Blood specimen collection device	13	15	3	8	39	2	2
27	Uric acid test system	13	15	2	8	38	2	2
28	spectrophotometer for clinical use	13	15	3	9	40	2	2
29	Extra oral source x-ray system	15	5	4	14	38	2	2
30	Intraoral source x-ray system	15	5	4	11	35	2	2
31	Dental chair and accessories	5	10	3	7	25	2	2
32	Boiling water sterilizer	0	5	1	7	13	1	1
33	Audiometer	5	15	1	3	24	2	2
34	Auditory impedance tester	5	15	2	3	25	2	2
35	Hearing Aid	5	15	1	3	24	2	2
36	Laryngostroboscope	5	5	1	3	14	1	1
37	Otoscope	5	5	1	3	14	1	1
38	electronic thermometer	5	15	2	3	25	2	2
39	infant radiant warmer	5	0	3	3	11	1	1
40	infant incubator	5	0	2	0	7	1	1

Table 2,
The Results After Training of the Proposed Network

	No. of cases	Accuracy of the network	Time
SOM	55	98%	1.3 S

7. Conclusions

In this paper, it has implemented a robust algorithm for risk priority assessment of medical equipments based on SOM and risk factor components. Three hundred and forty five reports were taken from two general hospitals in Baghdad. These reports are used for the calculation of the risk factor components. MATLAB software package version 7 was used to implement the software in the current work. Four risk components Equipments, function, physical risk, maintenance requirements and risk points) were calculated for the collected data sets. These components which represent the static and dynamic risk factors for the medical equipment. These risk components were carried out to generate training data for the SOM and to assess risk priority. These components are fed to the SOM network.

The accuracy is calculated to evaluate its effectiveness of the proposed network. The obtained accuracy of the network was found to be equal to 98%.

The biomedical engineer can use the proposed algorithm to deploy technical resources in a cost-effective manner. In addition to the direct economic benefits, safety is enhanced as problem equipment is identified and monitored more frequently. The integration of a proactive risk-assessment tool into the equipment management program with the use of NN can more accurately bring to focus technical resources in the health care environment..

Individually, the biomedical engineer cannot provide all the necessary components for managing risk in the health care environment. Using historical information reports of the medical device and the computer algorithms to only address equipment-related problems, after an incident, is not sufficient. The use of a proactive risk-management tool is necessary.

Based on the obtained accuracy, it can be concluded that that the proposed system gives faster and more accurate risk assessment compared with human work and acts as promising tool for assessing the risk factor in the service departments in large hospitals in Iraq. Also it will save the time and labor for the hospitals and eliminate the time consuming procedures for calculation of risk priority.

In summary, superior risk assessment within a medical equipment management program requires better use of computer algorithms, communication, and information analysis by the use of NN and distribution of the resulted risk priorities among all health care providers.

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مقترح خوارزمية لتقنية الذكاء الاصطناعي لتقييم اولويات الخطورة للاجهزة والمعدات الطبية في المستشفيات العراقية

علي حسين علي التميمي ، شذى كاظم عبد ، نبراس حسين غائب
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الخلاصة

يقدم البحث خوارزمية لتقييم اولويات الخطورة للاجهزة و المعدات الطبية في المستشفيات العراقية معتمدا على حساب عوامل الخطورة الساكنة والديناميكية وخرائط كوهونين ذاتية التنظيم. تم حساب اربع متغيرات خطورة ل 345 جهاز طبي مختلف. تم اخذ هذه العينات من مستشفى اليرموك التعليمي و مستشفى الشهيد عدنان للجراحات التخصصية في بغداد. تم حساب مكونات الخطورة الاستاتيكية (وظيفة الجهاز و الخطورة المادية) و مكونات الخطورة الديناميكية (متطلبات الصيانة و نقاط الخطورة).

هذه المكونات استعملت كمدخلات للشبكة العصيبية وهي من نوع خرائط كوهونيين الذاتية التنظيم. لاختبار كفاءة الخوارزمية، تم حساب نسبة التمييز للشبكة ووجد انه 98% ومن هذا البحث نستنتج النظام المقترح يعطي تقييم سريع ودقيق لاولوية الخطورة و يعمل كأداة واعدة لتقييم عامل الخطورة في اقسام الصيانة في المستشفيات الكبيرة في العراق.